Brain Tumor Detection using Machine Learning Algorithm

A Research Report
Submitted in partial fulfillment of the requirements for the Degree of
Bachelor of Science in Computer Science and Engineering

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Letter of Transmittal

10,02,2024

The Chairman,
Department of Computer Science and Engineering
Southeast University, Bangladesh
Tejgaon, Dhaka

Through: Supervisor, Tashreef Muhammad

Subject: Submission of Research Report

Dear Sir,
With due respect, we would like to submit our research report on A Study of Selected Classification Algorithms for Tumor detection. It was a great pleasure for us to work with such a captivating topic. By following instruction of yours and full-filling the requirements of Southeast University, this work has been performed. So, we have tried our level best to complete our research. We are requesting your kind approval of this report. Hope you will appreciate our hard work and excuse the minor errors.

Sincerely Yours,

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CANDIDATE'S DECLARATION

We, hereby, declare that the thesis presented in this report is the outcome of the investigation performed by us under the supervision of Tashreef Muhammad, Lecturer, Department of Computer Science and Engineering, Southeast University, Bangladesh. The work was done through CSE459: Research Methodology course, in accordance with the course curriculum of the Department for the Bachelor of Science in Computer Science and Engineering program.

It is also declared that neither this research nor any part thereof has been submitted anywhere else for the award of any degree, diploma or other qualifications.

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CERTIFICATION

This research titled, **"Brain Tumor Detection using Machine Learning Algorithm"**, submitted by the group as mentioned below has been accepted as satisfactory in partial fulfillment of the requirements for the degree B.Sc. in Computer Science and Engineering in February 10, 2024.

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Dhaka
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ABSTRACT

Brain tumor occurs owing to uncontrolled and rapid growth of cells. If not treated at an initial phase, it may lead to death. Despite many significant efforts and promising outcomes in this domain, accurate segmentation and classification remain a challenging task. A major challenge for brain tumor detection arises from the variations in tumor location, shape, and size. The objective of this survey is to deliver a comprehensive literature on brain tumor detection through magnetic resonance imaging to help the researchers. This survey covered the anatomy of brain tumors, publicly available datasets, enhancement techniques, segmentation, feature extraction, classification, and deep learning, transfer learning and quantum machine learning for brain tumor analysis. Finally, this survey provides all important literature for the detection of brain tumors with their advantages, limitations, developments, and future trends.

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Chapter 1

Introduction

The brain is a key organ responsible for the central nervous system. The human brain complements the central nervous system by connecting the bone marrow. The brain has the responsibility of controlling the actions of the human body. It receives the information from a different sense and after making decisions, sends the instructions to the body. The brain is the central part of the administration section of the human body that is responsible for all the activities of the human body with the help of neurons. Malignant and benign are the currently prevalent types of significant brain tumors. The brain tumor is considered deadly cancer in adults and children. A brain tumor occurs when the brain tissues develop unnaturally. The abnormal tissues overgrow compared to the healthy cells, causing the mass of cells that eventually transform tumors . A benign tumor is the least damaging type of tumor and has no tumor cells. Malicious cancer is tumor cells that can be very deadly and deliberate to be deadly. A malignant a tumor can affect the entire brain. Common primary tumors found among adults are glioma, meningioma, and pituitary. Gliomas come from glial cells that exist in the supporting tissue of the brain. Meningiomas are typically benign tumors that grow slowly and come from the outer shells of the brain just beneath the skull. Meningiomas are generally found in the cerebral hemispheres, and they can take several years to be detected. The pituitary gland is situated at the lower part of the brain. Its main function is to produce the hormones to control the various glands of the body, such as thyroid glands. A pituitary tumor may affect the operation of these glands (National Brain Tumor Society). Quick and timely recognition of a brain tumor is of the utmost importance for curing the tumor. It depends on the expertise and professional skills of the doctor and which method is selected to treat the patient for rapid recovery. It is challenging to determine the correct type of brain tumor in the initial phase, yet vital as it helps the physicians treat the patient accordingly. Gastrointestinal is the most commonly diagnosed type of cancer. It activates the gastrointestinal polyps. The method of diagnosis of gastrointestinal polyps is video endoscopy. A small camera enters the human body and is guided by the gastrointestinal tract

to reveal and exclude polyps. However, some polyps are considered undetected and may be malignant tumors at some point. To reduce the polyp mis-detection rate, “a computer-aided polyp detection system” should be used. Brain tumors can be a major contributor to psychiatric complications such as depression and panic attacks. Early detection of brain tumors has a significant impression on the success of tumor treatment. Gliomas are significant early brain tumors with an extremely high mortality occurrence ratio. Gliomas can be classified as High-Grade Gliomas (HGG), which are infiltrated and more destructive, or Low-Grade Gliomas (LGG), which are of little harm. It is chal-lenging to detect the tumor because it can appear in any shape, size, and location. Glioma is considered to be the more common type of brain tumor. MRI scans generally segment glioma in ne-crotic tissue, active tumor, and surrounding edema (ED). Manually segmenting tumors are a slow and repetitive procedure that requires the help of a human expert. Computerized tools play an essential role in glioma segmentation. Glioma segmentation algorithms can be typically distributed into traditional Machine Learning and Deep Learning algorithms. According to a study, a Deep Learning Algorithm (3D Dense UNet CNN) was proposed to classify the output in the whole tumor (WT), tumor core (TC), and enhancing tumor (ET). The processing of medical images plays a key role in assisting humans in identifying different diseases. Computer tomography (CT) and Magnetic Resonance Imaging (MRI) are two approaches usually utilized for inspecting the ir-regularities in brain tissues concerning the size, location, or shape of cells, which can help in detecting the tumor in its initial stages. Robust machine learning systems enhance the accuracy identification that supports clinicians in treatment. It is important to choose an effective algorithm with specific characteristics and classifiers to classify the tumor to achieve maximum efficiency. In contrast to traditional manual classification, algorithms are more efficient and accurate in classification.

This article proposes a new machine learning (ML) model to overcome this precise segmentation of brain tumors. The proposed intelligent detection model for identifying brain tumors has been classified into four classes: no-tumor, yes-tumor. A total of 4369 images have been used in the model, including 3566 for yes tumor class (glioma, meningioma, and pituitary) and 803 for the no-tumor class.

Deep learning replicates the brain in data processing, pattern recognition, and decision-making development. Deep neural networks have the competency of unsupervised learning from unstructured data. Convolutional Neural Network (CNN) works exceptionally well in deep learning, especially recognition and classification of images, speech, or text. Convolutional Network typically contains an inserting layer, a resulting layer, and many undiscovered layers. A series of convolutional layers are linked in the undiscovered layers. The starting function comprises the RELU layer, and the Final Convolution embroils the back-propagation.

1.1 Motivation

Brain Tumor are reported in people of all ages, races, and genders. Around one lac people are diagnosed with a primary brain tumor every year. Classification methods are very famous in various automatic medical diagnoses tools. So in this research we studied CNN algorithms. And develop a classification algorithm that can effectively analyze the available clinical and laboratory data to predict the absence of brain Tumor. Particularly, the study has the following sub-objectives:

- Learn more about classification algorithms.
- Learn more about brain tumors.
- Calculate the performance of classification algorithms.

1.2 Objective

In that methodology, Convolution Neural Network are employed for tumor detection. The proposed work of this manuscript utilizes for acquiring the features and RELU classifier is for tumor prediction. Brain tumors rarely become apparent at the group stage, even with treatment it may not be feasible to save lives. Our goal is to develop an AI model capable of detecting any symptoms associated with brain tumors.

1.3 Scope of Research

The research work can be used in the medical sector especially in the Brain tumor prediction section. Use of CNN classification algorithms will help to predict whether a patient is affected with a brain tumor or not. Some papers we have already developed AI models for detecting brain tumors. We want to create this model achieve better accuracy by utilizing MRI Image.

Chapter 2

Literature Review

This section highlights that detecting tumors of the brain with the help of machine learning and deep learning algorithms is an ongoing research area. A lot of work has already been carried out and researchers are continuously completing studies to improve this progress. In this section, the survey was made on the following sequences.

- Machine and deep learning algorithms.
- Morphological based segmentation methods.
- CNN based classification.

Shidong Li et al. [1] developed a Brain tumor segmentation based on region of interest-aided localization and segmentation U-Net . In this method, the authors applied The paper proposes a region-of-interest-aided (ROI-aided) deep learning technique for automatic brain tumor MRI segmentation.This nonlinear approach produced significant simulation results using the swarm optimization methodology. The authors obtained 87 % of tumor segmentation accuracy on open access BRATS 2015 dataset images.

Soheila Saeedi et al. [2] explored an MRI-based brain tumor detection using Convolutional deep learning methods. This method applied energy segmentation technique to the set of brain MRI images for identifying the tumor patterns. The segmented tumor patterns were classified into normal regions or abnormal tumor regions using KNN & SVM classification approach. This method attained the classification accuracy of gradually 86 % and 80 % for the brain MRI images on different sets of databases.

Francesco Mercaldo et al. [3] developed an Object Detection for Brain Cancer Detection and Localization .The paper utilizes the YOLO (You Only Look Once) model for automatic detection and localization of brain cancer from MRI scans. The proposed method involves analyzing brain MRIs and requires a dataset consisting of brain cancer MRIs with corre-

sponding annotations indicating the localization of cancerous regions. This model achieves 94% accuracy.

Saeedi, Soheila and Rezayi et al [2] In this paper, using three machine learning algorithms (KNN, SVM,RF) and one dataset to predict brain cancer.They collect the data then preprocess ,training and testing the data. By comparing this algorithm found the highest accuracy in K Nearest Neighbors.

Deependra Rastogi et al. [4] explored a Brain Tumor Detection and Localization: An Inception V3-Based Classification Followed By RESUNET-Based Segmentation Approach.(TCGA-GBM) dataset, which consists of MRI scans with masks. THis modelaccuracy is 96.50%.

J. N. Stember et al. [5] explored Reinforcement learning using Deep Q networks and Q Learning accurately localizes brain tumors on MRI with very small training sets. The RL approach shows progressive improvement in generalizability to a separate testing set over training time, reaching 70% accuracy, while the supervised approach performs poorly on the testing set with only 11

Maad M. Mijwil et al. [6] developed MobileNetV1-Based Deep Learning Model for Accurate Brain Tumor Classification. The MobileNetV1-based deep learning model achieved an accuracy result of more than 97

Hu, An et al [5]In this paper they use metaheuristics and deep learning to classify the brain tumor with an 88% accuracy. There main objective find the tumor at the beginning stage also find the tumor area using image processing

Almadhoun, Hamza Rafiq [7]In this Paper, Use Different deep learning model which give minimum error to increase accuracy. They use different deep learning performance to predict and prognosis of cancer and applied it on brain cancer datasets.Rapid diagnosis and detection of brain tumors.Reduce the cost of diagnosis and repetitive images.Increase proficiency using deep learning techniques to detect brain tumors.

Sarah Zuhair et al. [8] Using deep learning classify brain tumor classification, then using statistical information (standard deviation, mean, skewness) identify its cancerous or non-cancerous.

Chapter 3

Description of Research Work

3.1 Algorithms

There are a lot of algorithm, But for image dataset there there ae few algorithms. For example CNNs, RNNs, Object Detection ETC. In our research we custom CNNs as our model.

3.2 CNNs Model

Convolutional Neural Networks (CNN) are a type of multi-layer neural network that is meant to discern visual patterns from pixel images. In CNN, 'convolution' is referred to as the mathematical function. It's a type of linear operation in which you can multiply two functions to create a third function that expresses how one function's shape can be changed by the other. In simple terms, two images that are represented in the form of two matrices, are multiplied to provide an output that is used to extract information from the image. CNN is similar to other neural networks, but because they use a sequence of convolutional layers, they add a layer of complexity to the equation. CNN cannot function without convolutional layers.

In a variety of computer vision tasks, CNN artificial neural networks have risen to the top. It has picked people's interest in a variety of fields.

A convolutional neural network is made up of numerous layers, such as convolution layers, pooling layers, and fully connected layers, and it uses a backpropagation algorithm to learn spatial hierarchies of data automatically and adaptively. You will learn more about these terms in the following section.

3.3 Architecture of CNNs

Figure 4.1 is Arrchitecture of Basic CNNs model.

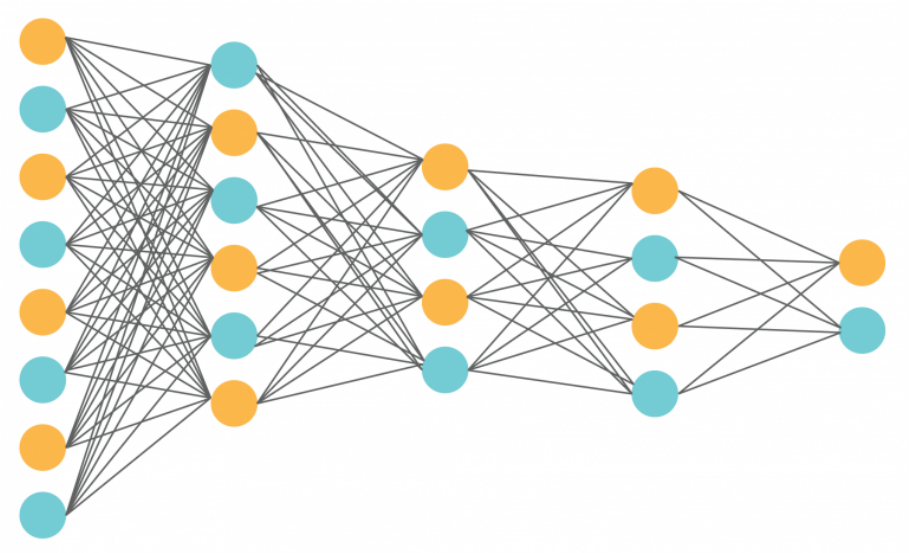


Figure 3.1: Demo for single image

The CNN job is to compress the images into a format that is easier to process while preserving elements that are important for obtaining a decent prediction. This is critical for designing an architecture that is capable of learning features while also being scalable to large datasets.

3.4 Convolutional Layer (CONV)

They are the foundation of CNN, and they are in charge of executing convolution operations. The Kernel/Filter is the component in this layer that performs the convolution operation (matrix). Until the complete image is scanned, the kernel makes horizontal and vertical adjustments dependent on the stride rate. The kernel is less in size than a picture, but it has more depth. This means that if the image has three (RGB) channels, the kernel height and width will be modest spatially, but the depth will span all three. A convolutional neural network, ConvNets in short has three layers which are its building blocks, let's have a look at **??** figure.

Other than convolution, there is another important part of convolutional layers, known as the Non-linear activation function. The outputs of the linear operations like convolution are passed through a non-linear activation function. Although smooth nonlinear functions such as the sigmoid or hyperbolic tangent (tanh) function were formerly utilized because they are mathematical representations of biological neuron actions. The rectified linear unit (ReLU) is now the most commonly used non-linear activation

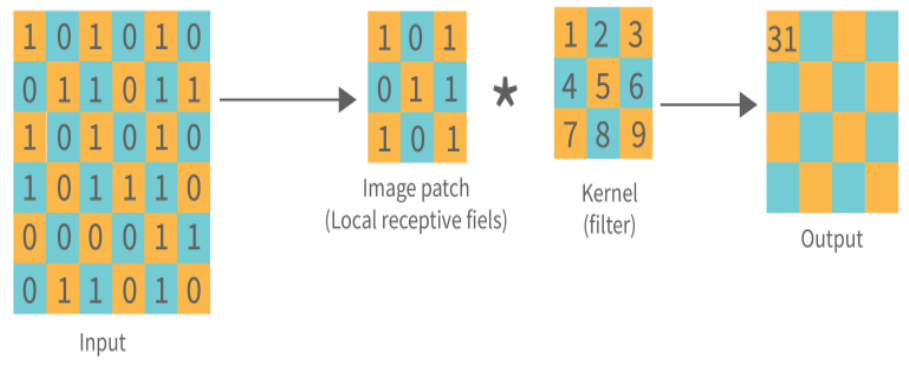


Figure 3.2: Convolutional Layer

3.5 Pooling Layer

This layer is in charge of reducing dimensionality. It aids in reducing the amount of computing power required to process the data. Pooling can be divided into two types: maximum pooling and average pooling. The maximum value from the area covered by the kernel on the image is returned by max pooling. The average of all the values in the part of the image covered by the kernel is returned by average pooling.

Figure 4.1 is Arrchitecture of Basic CNNs model.

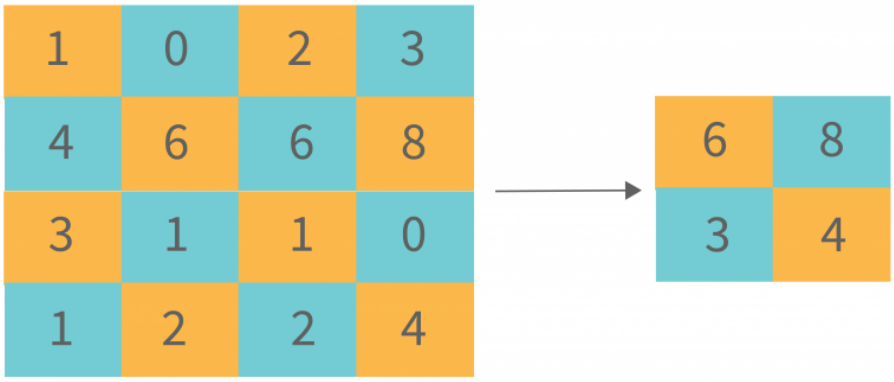


Figure 3.3: Demo for single image

3.6 Activation Function

Activation Function: The last fully connected layer's activation function is frequently distinct from the others. Each activity necessitates the selection of an appropriate activation function. The soft-max function, which normalizes output real values from the last fully connected layer to target class probabilities, where each value ranges between 0 and 1 and all values total to 1, is an activation function used in the multi-class classification problem.

3.7 Proposed Model

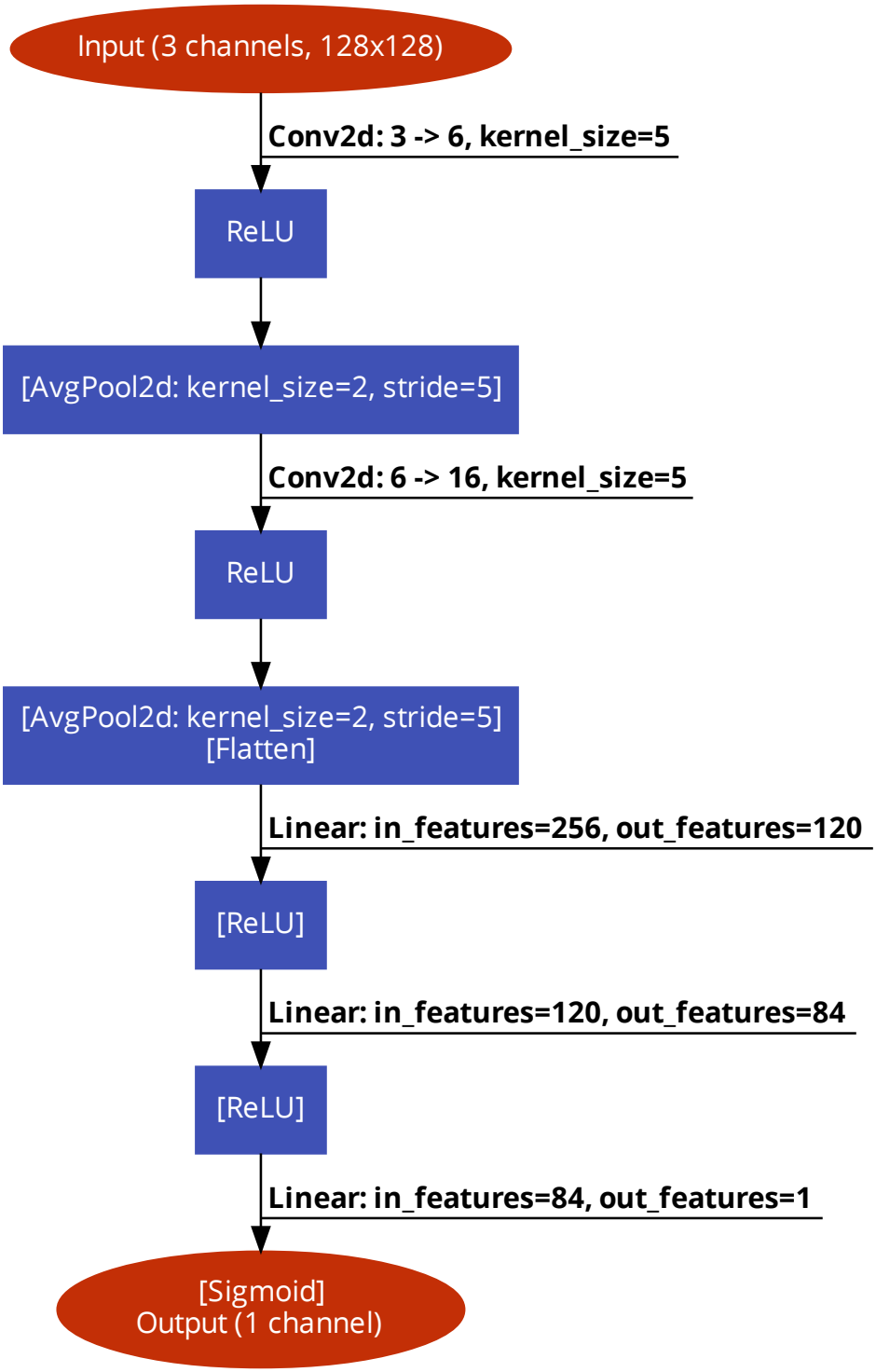


Figure 3.4: Proposed Model

Here's a step-by-step description of the architecture of proposed model model:

- Input Layer (3 channels, 128x128):

  Assumes input images with three color channels (RGB) and a size of 128x128 pixels.

- Convolutional Layer 1:

  Applies a convolutional operation with 3 input channels, 6 output channels, and a kernel size of 5x5. Followed by a Rectified Linear Unit (ReLU) activation function. Subsequently, an Average Pooling operation is applied with a kernel size of 2x2 and a stride of 5.

- Convolutional Layer 2:

  Applies a second convolutional operation with 6 input channels, 16 output channels, and a kernel size of 5x5. Followed by ReLU activation. Followed by Average Pooling with a kernel size of 2x2 and a stride of 5.

- Flatten Layer:

  Flattens the output from the previous layer into a 1D vector, preparing it for fully connected layers.

- Fully Connected Layer 1:

  Applies a linear transformation with 256 input features and 120 output features. Followed by a ReLU activation function.

- Fully Connected Layer 2:

  Another linear transformation with 120 input features and 84 output features. Followed by a ReLU activation function.

- Output Layer:

  Final linear transformation with 84 input features and 1 output feature. Followed by a Sigmoid activation function. The Sigmoid activation is commonly used for binary classification tasks to squash the output into the range [0, 1].

- Output (1 channel):

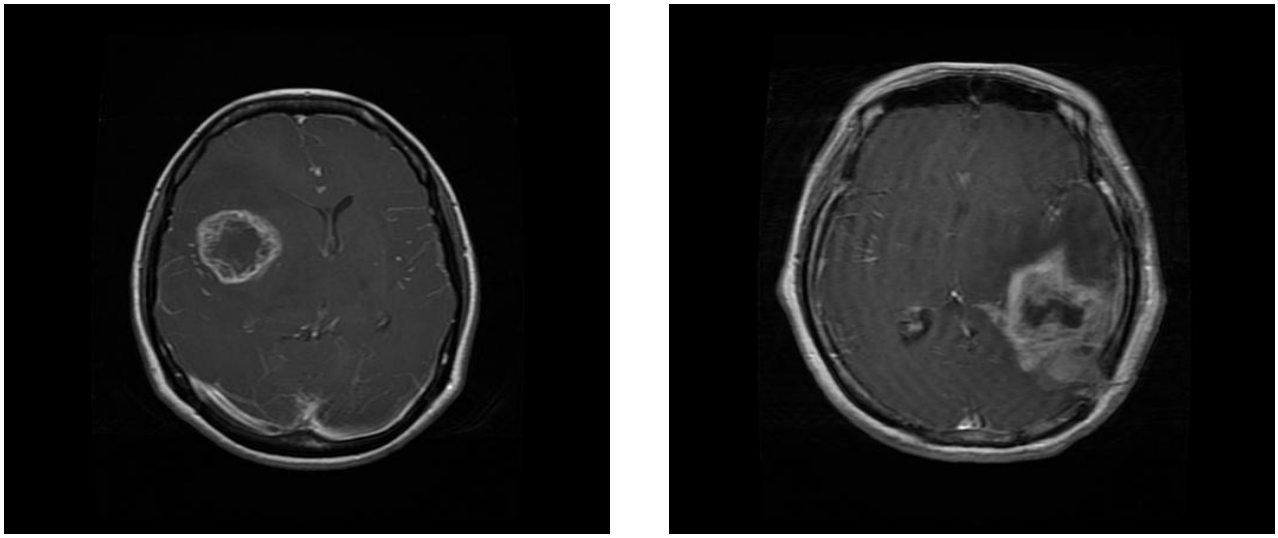
  The final output is a single-channel representing the predicted probability of belonging to the positive class (e.g., tumor present).

3.8 Dataset

We collect a Dataset that is an MRI dataset. There has 3566 images data that have tumor also there has 803 images that haven't any tumor or healthy images. Our dataset haven't any parameter like patient age, previous history etc. But we have image size, image channel.

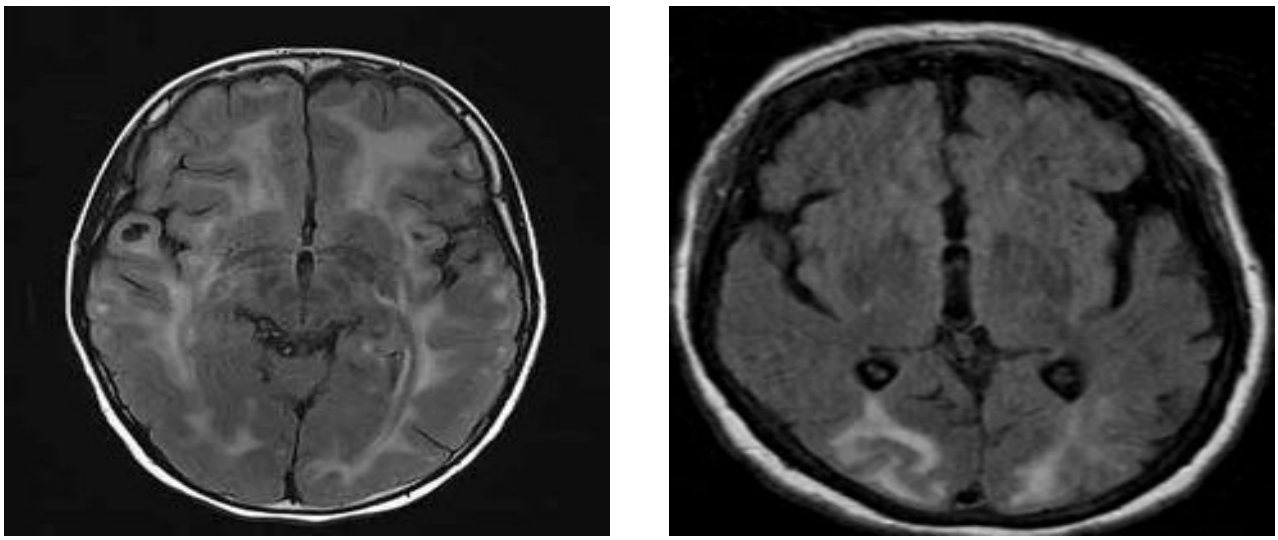
3.8.1 Data preview

Here is few data priview of our dataset.



(a) Tumor image (b) Tumor image

Figure 3.5: Tumor Images



(a) Non-Tumor image (b) Non-Tumor image

Figure 3.6: Non-Tumor Images

In the first two picture we saw there is tumor images. In the second two pic there is no tumor images. In the first picture we saw there is a tumor one the left side of the brain near middle of the brain. In the 2nd picture wee saw few fade area in the right side. The fade area can be healthy. But our model will differentiate every single possibility to detect correct prediction.

In the second two pic there has Non-tumor or healthy images. In the first pic we see there is an healthy image and there no spot of tumor. In the second picture we saw there is also a healthy image but there has few spot that can be tumor. Our target is to overcome this problem.

Chapter 4

Result and Decision

4.1 Result

This section evaluates the excellence of the introduced convolution neural network based brain tumor recognition from the MRI. In this work, the BRATS2015 dataset consists of 4369 brain images with “yes” and “no” folders. The labeled information is more helpful in classifying the testing images with maximum accuracy. The discussed system is implemented using CNN, RELU and the defined image processing and machine learning techniques are applied to recognize the tumor. In this work, the weighted median filter is applied to remove the noise from the MRI, which is more helpful in eliminating irrelevant and inconsistent details. The noise removal process reduces the computation complexity and difficulties in region segmentation.The introduced method investigates every region, which maximizes the inner details examination procedure. The effective utilization of segmentation procedures improves the overall tumor recognition accuracy. Traditional accuracy, precision, recall, and F1-score metrics are utilized to determine the system’s efficiency. The system effectiveness is evaluated using the prescribed performance matrices and the result shown in the table.

Method	Accuracy	Precision	Recall	F1-Score
CNN	0.98	0.96	0.98	0.97

Table 4.1: Accuracy Table

This process helps to reduce uncertainty issues while investigating the pixel region effectively. Moreover, the CNN has different layers that also segment the region in the pre-model.

According to the result, the graphical representation of the train loss and validation loss,

We use 1000 epoch in our model also our learning rate is 0.000001. In the starting our training and validation loss start form 0.67 and after 1000 epoch is 0.145. Figure 4.2 is the visual representation of Epoch 10 to epoch 1000.

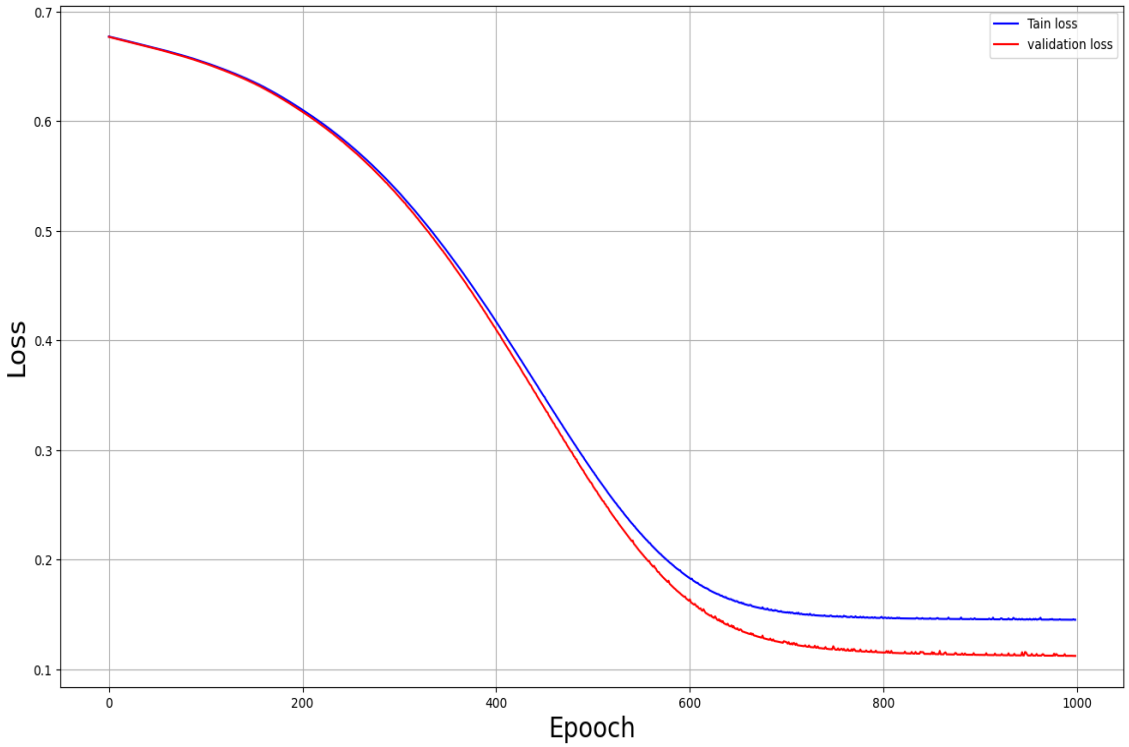


Figure 4.1: Error validation curve

```
Train epoch: 700        Loss: 0.151895
Train epoch: 710        Loss: 0.150839
Train epoch: 720        Loss: 0.149952
Train epoch: 730        Loss: 0.149675
Train epoch: 740        Loss: 0.148662
Train epoch: 750        Loss: 0.148171
Train epoch: 760        Loss: 0.147773
Train epoch: 770        Loss: 0.147418
Train epoch: 780        Loss: 0.147147
Train epoch: 790        Loss: 0.147406
Train epoch: 800        Loss: 0.147730
Train epoch: 810        Loss: 0.146944
Train epoch: 820        Loss: 0.146352
Train epoch: 830        Loss: 0.146241
Train epoch: 840        Loss: 0.146103
Train epoch: 850        Loss: 0.146581
Train epoch: 860        Loss: 0.145908
Train epoch: 870        Loss: 0.145819
Train epoch: 880        Loss: 0.145757
Train epoch: 890        Loss: 0.145680
Train epoch: 900        Loss: 0.145611
Train epoch: 910        Loss: 0.145552
Train epoch: 920        Loss: 0.145499
Train epoch: 930        Loss: 0.145431
Train epoch: 940        Loss: 0.145390
Train epoch: 950        Loss: 0.145773
Train epoch: 960        Loss: 0.145281
Train epoch: 970        Loss: 0.145248
Train epoch: 980        Loss: 0.145197
Train epoch: 990        Loss: 0.145169
Train epoch: 1000       Loss: 0.145110
```

(a) Till 1000 epoch

```
Train epoch: 10 Loss: 0.675541
Train epoch: 20 Loss: 0.673376
Train epoch: 30 Loss: 0.671227
Train epoch: 40 Loss: 0.669034
Train epoch: 50 Loss: 0.666803
Train epoch: 60 Loss: 0.664489
Train epoch: 70 Loss: 0.662072
Train epoch: 80 Loss: 0.659550
Train epoch: 90 Loss: 0.656879
Train epoch: 100        Loss: 0.653982
Train epoch: 110        Loss: 0.650874
Train epoch: 120        Loss: 0.647615
Train epoch: 130        Loss: 0.644137
Train epoch: 140        Loss: 0.640485
Train epoch: 150        Loss: 0.636504
Train epoch: 160        Loss: 0.632162
Train epoch: 170        Loss: 0.627465
Train epoch: 180        Loss: 0.622449
Train epoch: 190        Loss: 0.617100
Train epoch: 200        Loss: 0.611503
Train epoch: 210        Loss: 0.605647
Train epoch: 220        Loss: 0.599503
Train epoch: 230        Loss: 0.593023
Train epoch: 240        Loss: 0.586175
Train epoch: 250        Loss: 0.578917
Train epoch: 260        Loss: 0.571277
Train epoch: 270        Loss: 0.563236
Train epoch: 280        Loss: 0.554784
Train epoch: 290        Loss: 0.545800
Train epoch: 300        Loss: 0.536410
Train epoch: 310        Loss: 0.526565
Train epoch: 320        Loss: 0.516240
```

(b) From 10 epoch

Figure 4.2: Epoch

Chapter 5

Conclusion

In this research work “Brain Tumor Detection using Machine Learning Algorithm” has been explained and analyzed. We have applied four selected classification algorithms CNNs, on a MRI dataset titled “Brain MMRi dataset” found in the Kaggle. The dataset has total 40369 images. At the end it is concluded that we have made efforts on the following points: We have applied modified CNNs classification algorithms on the dataset We have measured and calculated the Accuracy, Sensitivity, Precision and Specificity of these algorithms. We have found CNNs algorithm has the highest Accuracy 0f 98.06 percent.

5.1 Future Work

In the future, we plan to apply proposed model on larger datasets. Also we want more algorithms to compare our model. We may also add more classification algorithms in our work. Also we want to localize the tumor area.

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